Forecasting Ramps of Wind Power Production at different time scales

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***Abstract* - Today, there is a growing concern in developping short-term wind power forecasting tools able to provide reliable information about particular, so-called "extreme" situations. One of them is the large and sharp variation of the production a wind farm can experience within a few hours called *ramp event*. Developping forecast information specially dedicated to ramps is of primary interest both because of the difficulties usual models have to predict them, and the potential risk they represent in the management of a power system. This paper presents two methods to forecast ramps at two different time scale. For the short-term (up to 2 or 3 days ahead), we estimate the uncertainty in the timing of ramps with time-oriented prediction intervals. Such intervals are derived from meteorological ensemble forecasts. Our second approach is dedicated to the very short-term (up to a few hours ahead) and use a propagation modelling of ramps to forecast ramps from the most up to date spatio-temporal information.**

***Key words* : wind power forecasts, ramps, phase errors, forecasts ensemble.**

1 Introduction

Forecasts of wind power generation are of primary interest in supporting wind power integration. They can facilitate several management operations, from wind energy trading at the electricity markets, to dispatching operations performed by the transmission system operators. Wind power short-term forecasting (up to 2 or 3 days ahead) often involves the statistical modelling of the relation between meteorological forecasts, wind power measurments, and the expected future production. When taking the form of a single value for a given location and lead time, these forecasts often referred as deterministic of point forecasts. Two extensive reviews on the state-of-the-art in wind power forecasting are available in [10] and [6].

In many areas of forecasting, both theoretical and practical developments are more and more going towards various forms of probabilistic forecasting. Probabilistic forecasting refers to the estimation of the uncertainty associated to point forecasts, or more generally to the predictibility of the considered stochastic process. For example, Pinson and Kariniotakis [21] have described two complementary approaches that consist in providing forecast users with skill forecasts (commonly in the form of risk indices [23]) or alternatively with confidence intervals. Various approaches can be found in the literature related to wind power forecasting. They may be either derived from meteorological ensembles [18, 17, 22], based on physical considerations [14], or finally produced from one of the numerous statistical methods that have appeared in the literature, see [4, 11, 15, 13, 16] among others. The benefits from probabilistic forecasting and related stochastic decision-making has been demonstrated based on case-study applications, e.g. for the optimal trading of wind power generation [20], dynamic reserve quantification [9], or for the optimal operation of combined wind-hydro power plants [5, 1].

Today, more and more end-users ask for dedicated tools, able to provide relevant information, with respect to specific situations (sometimes referred as "'extreme events"'). Such situations may be related to particular meteorological events (such as thunderstorms or tornadoes), to some features in the statistical properties of the wind generation process (e.g. periods of severe variability or of abrupt changes the average power production level), or to large forecasting errors [19]. In any case, the considered situations may have negative (potentially large) impacts affecting the power system security or the benefits of producers. One particular example of such situations may be the sharp and large changes in the production level, so-called *ramp events*. It has been pointed out the need in reliable information with respect to the timing, duration, magnitude and finally the likelihood of such events [19].

Recently, the authors proposed a definition and a forecasting methodology of ramps for a single wind farm and look ahead times up to 72 hours ahead [2, 3]. Improving the forecast accuracy of ramps for the longuest term may not be efficiently performed, even with advanced statistical methods. Indeed errors in the timing (phase errors) or more generally the occurrence of ramps, are then mainly related to the limited performances of Numerical Weather Prediction models to forecast underlying meteorological conditions. Following our work in [3], we show how a probabilistic approach based on meteorological ensemble, can be used to reliably forecast the occurrence of ramps. Some results are depicted in Section 3. For the shortest-term (up to 15mn to 5 hours ahead), the sparsity of meteorological forecast runs do not allow to forecast ramps with the most up to date information. Indeed, such forecasts are generally updated every 3 to 6 hours, while a weather system can propagate through a geographic area like western Denmark within 1 to 2 hours. We then explore how the information provided by 15mn scada measurments at a large number of wind farms spread all over such an area can be used to improve ramp forecasting. In Section 4, we propose a model in which the spatio-temporal propagation of ramps is incorporated and show how it may improve the forecasting of ramps. The definition of ramps we proposed in [2, 3] is beforhand described in Section 2.

2 Definition of ramps

Several definitions of a ramp exist in the literature related to wind energy [7, 12, 8, 3]. In [3], we reviewed the main ones and discussed how to properly define (and then detect) a ramp from a wind power time series. The proposed methodology relies on the significant literature of signal processing, in which identifying large variations (referred as edges) of a signal has been studied for a while (for a literature overview we refer to [24]). As a result, our definition performs a characterization of a ramp through a set of three parameters: the *support* (duration), the *timing* and the *intensity* of the ramp. Such characterization is achieved following a 3 steps methodology:

1. **Step** 1 First, we estimate the variations of the production through using a derivative filter, which combines smoothing and differentiating of the power signal:

$$f_t = \frac{1}{n}\sum_{h=1}^{n} p_{t+h} - \frac{1}{n}\sum_{h=1}^{n} p_{t+h-n} \qquad (1)$$

where p_t and f_t respectively denote a wind power time series and its filter's response. The parameter n represents both the order of the moving average smoothing filter and the lag of finite differences. It has to be fixed according to the time scale at which the variations are considered as ramps. We used a value of $n = 5$ hours in our study.

2. **Step** 2. A ramp is associated to each local extremum of the filtered signal larger (in absolute value) than a given threshold: $|\, f_t \,| \geq \tau$. The threshold τ represents the minimum intensity of a power variation to be considered as a ramp. One has to notice here that decreasing variations corresponds to negative values of the filtered power (so a decreasing ramp is detected when one has $f_t \leq -\tau$). We considered a value of $\tau = 25\%$ of the nominal capacity in this work.

3. **Step** 3. Once a ramp is detected, we are able to characterize it through its support: the time interval during which the absolute value of the

filtered signal f_t lies above τ. The timing and intensity of the ramp are given by the coordinates of the filtered power local extremum (t_r, f_{t_r}) (such that f_{t_r} is the maximum value of $|f_t|$, for t in the support of the ramp).

3 Warning for ramp occurrence using temporal prediction intervals

3.1 Introduction

As we already said, the timing and more generally the occurrence of ramps may be improperly forecast because of the difficulties Numerical Weather Prediction models have to catch underlying weather conditions. With state-of-the-art wind power forecasting models, it is common to forecast a ramp either to soon or to late, or to not forecast it at all. Then, it is of primary concern to estimate the likelihood of a ramp to occur along with the temporal uncertainty. Such information may be contained in meteorological forecast ensembles. Through introducing perturbations in the estimation of the initial state of the atmopshere, meteorological institutes (such as ECMWF), are able to provide different forecast scenario of its evolution. Such scenario are expected to represent various forms of uncertainty in the development of weather systems. When converted to power ensemble forecasts, one may expect to get scenario of wind generation carrying some information about the ramp occurrence and timing uncertainty. We used wind power ensemble forecasts as an entry to our forecasting procedure. These ensembles have been obtained through using wind ensemble from the EPS of ECMWF and the statistical procedure random forest as described in [2].

3.2 Forecasting procedure

Firstable, we forecast different scenario of the production variations, through applying the derivative filtering described in (1) to the members of a wind power forecast ensemble. Then, we get an ensemble of forecast ramps through thresholding. Afterwards, we cluster the forecasts from different ensemble members, which are identified as corresponding to a same event. Finally, each forecast event is characterized by the number of members N forecasting it, and the average timing t computed from the ensemble of forecast timings of the associated cluster.

Our estimation of the temporal uncertainty of ramp occurrence take the form of prediction intervals I_δ centered on the mean timing t and of fixed width 2δ. We then model the probability for a ramp to occur in I_δ, as a function of N: $\mathbb{P}\,(Ramp \in I_\delta \,|\, N) = g(N)$. Estimating g turns out to be a regression problem, we computed probability forecasts from both a logistic model and a kernel-based Nadarya-Watson estimator. For more details on the procedure we refer to [3].

To characterize the distribution of ramp timing errors, we apply the proposed methodology for a set of interval radius $\delta = 1, ..., 8$ hours. The resulting product of our estimations are shown in Figure 1

3.3 Results

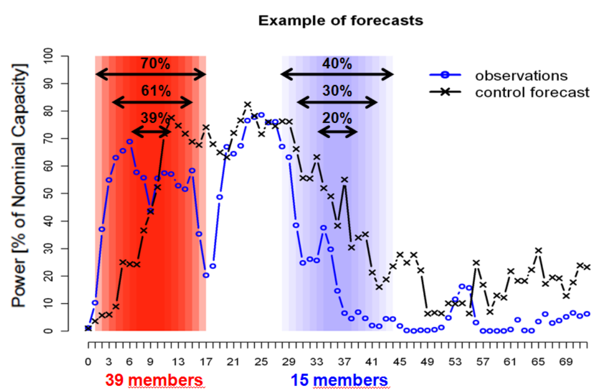

Figure 1: Prediction intervals I_δ, $\delta = 1, \ldots, 8$ hours for an increasing ramp forecast by 39 members, followed by a decreasing one forecast by 15 members. Probability forecasts (given in percentages at the top of the figure) have been made with a rectangular kernel and a nearest-neighboor bandwidth selection procedure. The change in forecast probability values depending on the forecast conditions (e.g. the value of N) illustrates well the resolution property of the proposed methodology.

We tested our procedure on three wind farms located in France. Our data cover the period from July 2004 to December 2005. For each model (logistic, kernel-based), we evaluated the reliability of our forecasts, e.g the property to get forecast probabilities close to observed frequencies, through reliability diagrams. The resolution property of our approach, e.g the ability to provide situation-dependent forecasts (which vary with N), has also been investigated. Our study shows that our methodology can provide reliable and situation-dependent forecasts. Results for estimations performed with a tricube kernel, at a wind farm embedded in a complex terrain are shown in Figure 2. The figure on the left shows the estimated probabilites (e.g estimation of g). As expected such probabilities increase with the number of members N forecasting a ramp. Our forecasts turned out to be reliable as shown by the reliability diagram on the right panel.

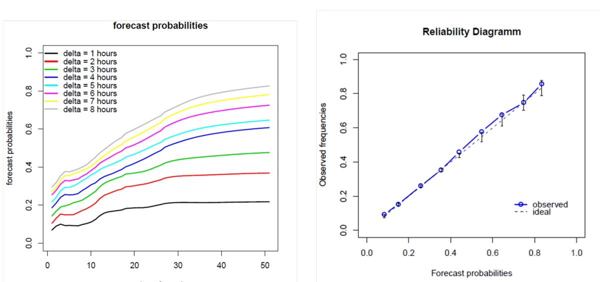

Figure 2: Estimated probabilities (left) and reliability diagram (right), for a wind farm located in France. Probability forecasts have been computed using a tricube kernel.

4 Propagation modelling to improve the very-short term forecast of ramps

4.1 Introduction

Let us now consider our second approach, which is dedicated to the forecasting of ramps for the shortest term (to a few ten of minutes up to a few hours ahead). It is essential when forecasting at this temporal scale to use the most up to date information. Our purpose is to build up a model which can rely on data of high temporal resolution, from wind farms covering a large geographical area. In this section, we consider transformation stations (assimilated as wind farms) from the Western Denmark. The corresponding wind power field is composed by measurements from about 200 different locations, with a 15 minutes temporal resolution.

A preliminary correlation analysis showed a mainly westerly propagation of ramps through Western Denmark. Then, we decided to study how some past upwind (e.g. from west) information about ramps could be useful in forecasting ramps at a downwind (e.g. at east) farm.

4.2 Modelling the propagation of ramps

For now, we have focused on a downwind farm located in the south-east of Western Denmark. Let us denote by p_t the probability for a ramp to be happening 3 hours ahead, and by $\hat{f}_t$ the filtered forecast production at the same horizon. The probability p_t can be estimated from the filtered forecast production $\hat{f}_t$ through a simple logistic model:

$$\log\left(\frac{p_t}{1-p_t}\right) = \alpha + \beta \hat{f}_t \tag{2}$$

This simple modelling, with no further information except from the considered downwind farm, will serve as a reference model.

To improve this model, we consider the past filtered production at some upwind farms as additionnal information. For the instant $t-i$, we choose to introduce this information through the quartile of the filtered forecast production $q_i(l)$ of farms located along a longitude l. We used the upper quartile when forecasting increasing ramps and the lower quartile otherwise. Assuming a fixed propagation speed v (expressed in longitude degrees in (3)), the propagation is then modeled through a wave model:

$$\log\left(\frac{p_t}{1-p_t}\right) = \alpha + \beta \hat{f}_t + \sum_i \gamma_i q_i(l_0 - vi) \qquad (3)$$

where i is a time delay ranging from 0 minute to 3 hours with a 15 minutes resolution, and l_0 is the downwind farm's longitude. Our model assumes a westerly propagation of ramps. Indeed, for a time delay i the considered upwind farms are located along the longitude $l_0 - vi$. Our preliminary analysis did not underline a preferred propagation speed. Then, we investigated the performances of our model for a range of values.

4.3 Results

We investigated the performances of our models both in terms of Brier Score (BS) and Area Under the Relative Operating Curve (AUC). The improvement of our propagation model (3) with respect to our reference model (2) are displayed in Figure 3. We observe significant improvements only in the case of increasing ramps. The differences between increasing and decreasing ramps results must have meteorological causes that will be further investigated. Once again the results do not underline any preferred propagation speed. Ramps must propagate at different and/or variable speeds. More improvements should be expected from modelling which does not assume a fixed propagation speed.

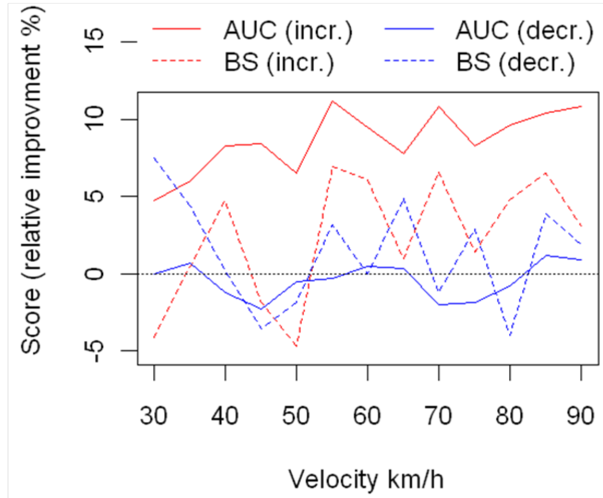

Figure 3: Improvments in terms of Brier Score (BS) and Area under the ROC Curve (AUC) of our propagation model (3) with respect to our reference model (2). Improvements are more significant for increasing ramps (red) than for decreasing ones (blue).

5 Conclusions

Large variations of the wind power production so-called ramp events represent challenging periods in the management of power systems. Since a few years, concerns have been raised about the need to develop dedicated forecasting tools. In this paper, we have introduced two forecasting approaches of ramps related to two different time scales.

When forecasting up to 2 or 3 days ahead, significant improvements in forecasting ramps would require increased performances from numerical weather models. It is nevertheless possible to increase the value of ramp forecasts through a reliable estimation of their temporal uncertainty. We proposed an approach to forecast ramps from meteorological ensembles, with time-oriented prediction intervals. The considered temporal scale is related to what we call **warning**, since the information provided by this type of forecast is not calling for a decision but helps being prepared to take one. For example, a large confidence interval on phase errors may induce more care from the operator than usual.

For the shortest term (up to a few hours), **alerting** forecasts must benefit from the most up to date information. In such context, we have proposed a model to improve the forecasting of ramps from the modelling of their propagation. We have presented preliminary encouraging results, as well as area of further investigations.

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References

[1] J.M. Angarita and J. Usaola. Combining hydro-generation and wind energy biddings and operation on spot electricity markets. *Electric Power Systems Research*, 77(5-6):393–400, 2007.

[2] A. Bossavy, R. Girard, and G. Kariniotakis. Forecasting uncertainty related to ramps of wind power production. In *Proc. of the 2010 European Wind Energy Conference, Warsaw, Poland*, 2010.

[3] A. Bossavy, R. Girard, and G. Kariniotakis. Forecasting ramps of wind power production with meteorological ensembles. Submitted. to the Wind Energy Journal, 2011.

[4] J.B. Bremnes. A comparison of a few statistical models for making quantile wind power forecasts. *Wind Energy*, 9(1-2):3–11, 2006.

[5] E. Castronuovo and J. PecasLopes. On the optimization of the daily operation of a wind-hydro power plant. *IEEE Transactions on Power Systems*, 19(3):1599–1606, 2004.

[6] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, and E. Feitosa. A review on the young history of the wind power short-term prediction. *Renewable and Sustainable Energy Reviews*, 12(6):1725 – 1744, 2008.

[7] N. Cutler, M. Kay, K. Jacka, and T.S. Nielsen. Detecting, categorizing and forecasting large ramps in wind farm power output using meteorological observations and wppt. *Wind Energy*, 10(5):453–470, 2007.

[8] N.J. Cutler. *Characterizing the Uncertainty in Potential Large Rapid Changes in Wind Power Generation*. PhD thesis, Electrical Engineering & Telecommunications, Faculty of Engineering, UNSW, 2009.

[9] R. Doherty and M. O'Malley. A new approach to quantify reserve demand in systems with significant installed wind capacity. *IEEE Transactions on Power Systems*, 20(2):587–595, 2005.

[10] G. Giebel, G. Kariniotakis, and R. Brownsword. State of the art on short-term wind power prediction. ANEMOS Deliverable Report D1.1, available online: http://anemos.cma.fr, 2003.

[11] G. Gneiting, K. Larson, K. Westrick, M. Genton, and E. Aldrich. Calibrated probabilistic forecasting at the stateline wind energy center: The regime-switching space-time method. *Journal of the Americal Statistical Association*, 101(475):968–979, 2006.

[12] B. Greaves, J. Collins, J. Parkes, and A. Tindal. Temporal forecast uncertainty for ramp events. *Wind Engineering*, 33:309–319(11), June 2009.

[13] J. Juban, N. Siebert, and G. Kariniotakis. Probabilistic short-term wind power forecasting for the optimal management of wind generation. In *Proc. of the IEEE PowerTech 2007 Conference, IEEE Conference, Lausanne, Switzerland*, 2007.

[14] M. Lange and U. Focken. *Physical Approach to Short-Term Wind Power Prediction*. Springer, 2005.

[15] J.K. Møller, H.Aa. Nielsen, and H. Madsen. Time adaptive quantile regression. *Computational Statistics and Data Analysis*, 52:1292–1303, 2008.

[16] H.Aa. Nielsen, H. Madsen, and T.S. Nielsen. Using quantile regression to extend an existing wind power forecasting system with probabilistic forecasts. *Wind Energy*, 9(1-2):95–108, 2006.

[17] H.Aa. Nielsen, T.S. Nielsen, H. Madsen, J. Badger, G. Giebel, L. Landberg, K. Sattler,

L Voulund, and J. Tøfting. From wind ensembles to probabilistic information about future wind power production - results from an actual application. In *Proc. of the IEEE PMAPS 2006 Conference, IEEE Conference, Probabilistic Methods Applied to Power Systems, Stockholm, Sweden*, 2006.

[18] H.Aa. Nielsen, T.S. Nielsen, H. Madsen, and K. Sattler. Wind power ensemble forecasting. In *Proc. of the 2004 Global Wind Power Conference, Chicago, Illinois (US)*, 2004.

[19] Pinson and the Safewind Consortium. Catalogue of complex to extreme situations. Technical report, 2010.

[20] P. Pinson, C. Chevallier, and G. Kariniotakis. Trading wind generation from short-term probabilistic forecasts of wind power. *IEEE Transactions on Power Systems*, 22(3):1148–1156, 2007.

[21] P. Pinson and G. Kariniotakis. On-line assessment of prediction risk for wind power production forecasts. *Wind Energy*, 7(2):119–132, 2004.

[22] P. Pinson and H. Madsen. Ensemble-based probabilistic forecasting at horns rev. *Wind Energy*, 12(2):137–155, 2009.

[23] P. Pinson, H.Aa. Nielsen, H. Madsen, and G. Kariniotakis. Skill forecasting from ensemble predictions of wind power. *Applied Energy*, 86(7-8):1326 – 1334, 2009.

[24] D. Ziou and S. Tabbone. Edge detection techniques - an overview. *International Journal of Pattern Recognition and Image Analysis*, 8:537–559, 1998.